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Review

Research Progress and Development Trend of Prognostics and Health Management Key Technologies for Equipment Diesel Engine

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Abstract: The diesel engine, as the main power source of equipment, faces practical problems in the maintenance process, such as difficulty in fault location and a lack of preventive maintenance techniques. Currently, breakdown maintenance and cyclical preventive maintenance are the main means of maintenance support after a diesel engine failure, but these methods require professional maintenance personnel to carry out manual fault diagnosis, which is time-consuming. Prognostics and health management (PHM), as a new technology in the field of equipment maintenance support, has significant advantages in improving equipment reliability and safety, enhancing equipment maintenance support capability, and reducing maintenance support costs. In view of this, when introducing PHM into diesel engine maintenance support, the research progress and development trend of the key technologies of PHM for diesel engines are carried out with the objective of achieving precise maintenance and scientific management of diesel engines, and the key technologies demand traction. Firstly, the development history of PHM technology is reviewed, and its basic concept and main functions are introduced. Secondly, the system architecture of PHM for diesel engines is constructed, and its key technologies are summarized. Then, the research progress in the field of PHM for diesel engines is reviewed from four aspects: data acquisition, data processing, fault diagnosis, and health status assessment. Finally, the challenges faced by diesel engine PHM in engineering applications are analyzed, effective solutions to address these challenges are explored, and the future development trend is foreseen.

Keywords: diesel engine; reliability; prognostics and health management; data acquisition; data processing; fault diagnosis; health status assessment

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1. Introduction

As the power system of self-propelled artillery, tanks, armored vehicles, and other weapons and equipment in the army's active equipment, diesel engines have the advantages of high torque and good economic performance. However, due to its complex structure and harsh working environment, reliability and safety gradually decrease with the increase in running time. If the failure of the diesel engine cannot be found in time to assess its health status, it will affect the performance of the equipment and even cause serious economic losses and safety accidents. According to statistics, in tank failure accidents, mechanical failure accounted for 35%, of which 48% were caused by diesel engine failure [1]. Currently, breakdown maintenance and cyclical preventive maintenance are the main means of maintenance support after a diesel engine failure, but these methods require professional maintenance personnel to carry out manual fault diagnosis, which is time-consuming. In addition, as a complex reciprocating machine, the diesel engine has multiple stages of health status, from normal operation to downtime, so how to effectively characterize and evaluate the different health status of the diesel engine during operation is a key issue that needs to be addressed in the actual maintenance support process of the diesel engine [2].

To effectively ensure the safe and reliable operation of equipment and economic maintenance, prognostics and health management (PHM) came into being. Previously, equipment maintenance support methods have been developed in four stages: breakdown maintenance, periodic preventive maintenance, condition maintenance, and predictive maintenance. However, the above traditional maintenance methods and concepts have the problem of being difficult to determine the maintenance intervals, difficult to meet the current new situation of equipment maintenance support needs, and requiring active exploration of the new theory and new technology applicable to the maintenance support of new and complex equipment. PHM integrates the ideas of condition maintenance and predictive maintenance, through sensing equipment status information, diagnosing equipment fault types, assessing equipment health status, predicting equipment remaining life, taking timely measures before the occurrence of faults, realizing effective diagnosis and early prevention of equipment faults, and ensuring equipment reliability and safety [3]. PHM extends traditional built-in test (BIT) techniques, external test equipment, fault monitoring, and diagnostic techniques, places greater emphasis on predicting future health status, changes reactive maintenance activities into pioneering maintenance support activities, and greatly improves the combat readiness of equipment. In summary, PHM is a maintenance support technology to enhance equipment management and support capabilities, improve the general quality characteristics of equipment, reduce whole life costs, and achieve scientific management of equipment information and maintenance resources in the information age. It is also the key development direction for future intelligent equipment operation and maintenance management.

Based on the above analysis, this paper takes the diesel engine, which is the main power source of the equipment, as the research object and aims at achieving the precise maintenance and scientific management of the diesel engine, focusing on the research progress and development trend of the key technologies of diesel engine PHM. It constructs the system architecture of diesel engine PHM, sorts out the key technologies of the diesel engine PHM, reviews the research status and hotspots of key technologies of diesel engine PHM, discusses the main existing problems, foresees the future research direction in the field of diesel engine PHM, and analyzes the possible solutions.

The literature in the review was mainly obtained through the China National Knowledge Infrastructure (CNKI) and Web of Science (WOS) databases. The review uses diesel engine PHM, reliability, diesel engine data acquisition (vibration signals, sound signals, infrared thermography, oil analysis, etc.), data processing (signal noise reduction, fault feature extraction, feature dimensionality reduction, etc.), diesel engine fault diagnosis, and diesel engine health status assessment as search keywords. A large amount of literature is available after searching for the above keywords. However, not all of the literature obtained is valuable, and redundancy is high. In order to enhance the referability of this review, the authors first restricted the search to the last three years. Secondly, the abstracts and conclusions of the obtained literature were read one by one, and those that were highly innovative as well as valuable were selected, and those that used similar methods were retained on a merit basis, in an attempt to streamline the full paper while covering all feasible methods. Finally, the selected literature was further assessed for its applicability, and the final literature required was summarized to obtain the literature analyzed in this review.

2. PHM Architecture for Diesel Engine Equipment

The composition of diesel engine equipment structure as shown in Figure 1 is mainly determined by the body group, two major structures (the crank rod structure and the gas distribution structure), and five systems (the intake and exhaust systems, fuel supply system, the lubrication system, the cooling system, and the starting system).

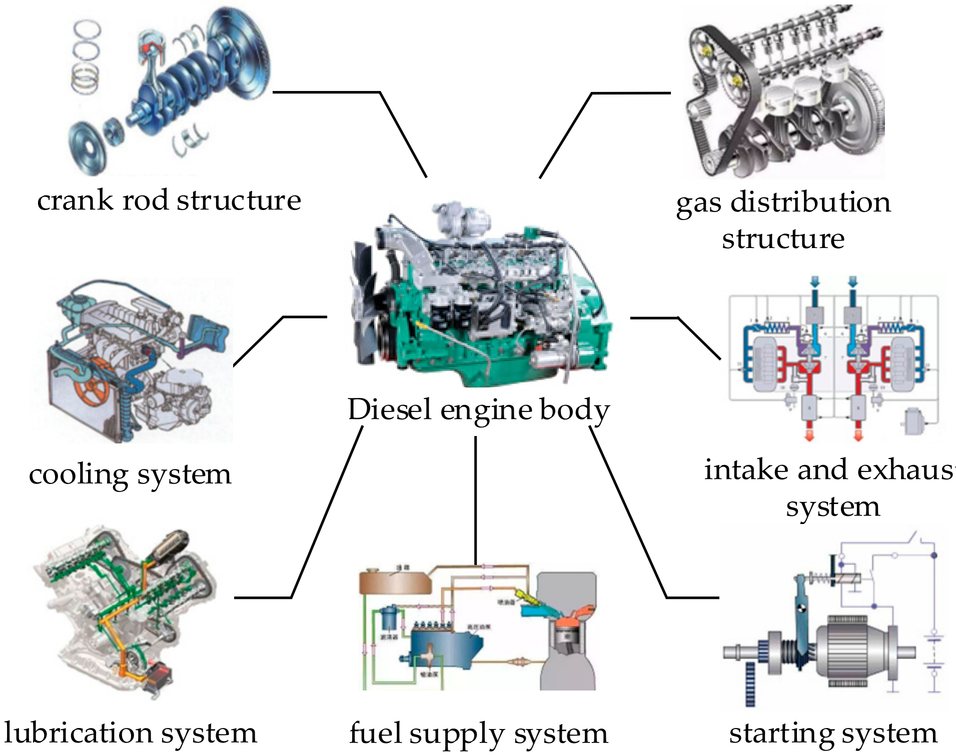


Figure 1. Schematic diagram of diesel engine components.

With the demand for diesel engine maintenance support as the driving force, PHM is introduced into diesel engine maintenance support to improve operational reliability and reduce the maintenance cost of diesel engines. Based on the existing achievements of the laboratory and with reference to condition-based maintenance under the open system architecture the relevant standards of the ISO 13373 to ISO 13381 series and the IEEE 1232 series standards, a generalized, standardized, and practical PHM system architecture for diesel engines is constructed as shown in Figure 2. The architecture enables a holistic consideration of diesel engine data acquisition, data processing, fault diagnosis, health status assessment, life prediction, and maintenance decision-making.

As can be seen from Figure 2, the PHM architecture for diesel engine equipment mainly consists of a data acquisition layer, a data processing layer, a fault diagnosis layer, a health assessment layer, a life prediction layer, a decision support layer, and a decision-making advice layer. Firstly, data reflecting the operating status of the diesel engine, such as vibration, sound, infrared thermal images, oil, etc., is collected through the data acquisition system. However, due to the complex operating environment of diesel engines and the interference of various components with each other, the data collected through sensors is inevitably of poor quality. Therefore, effective data processing methods are needed to guarantee data quality, including signal noise reduction, fault feature extraction, feature dimensionality reduction, etc. Secondly, the processed data can be fed into the fault diagnosis layer to correctly indicate fault location on the one hand, and the extracted feature parameters can be used in the health assessment layer to realize the classification of health classes and identification of degradation status of the diesel engine, as well as in the life prediction layer to predict the location, time, and remaining life of the diesel engine when a fault occurs. Finally, the fault diagnosis results, degradation status identification results, health status assessment results, remaining life prediction results, and maintenance support resources are comprehensively analyzed, and the decision support layer and decision-making advice layer are used to formulate the maintenance support plan for the diesel engine according to the maintenance tasks and give maintenance recommendations.

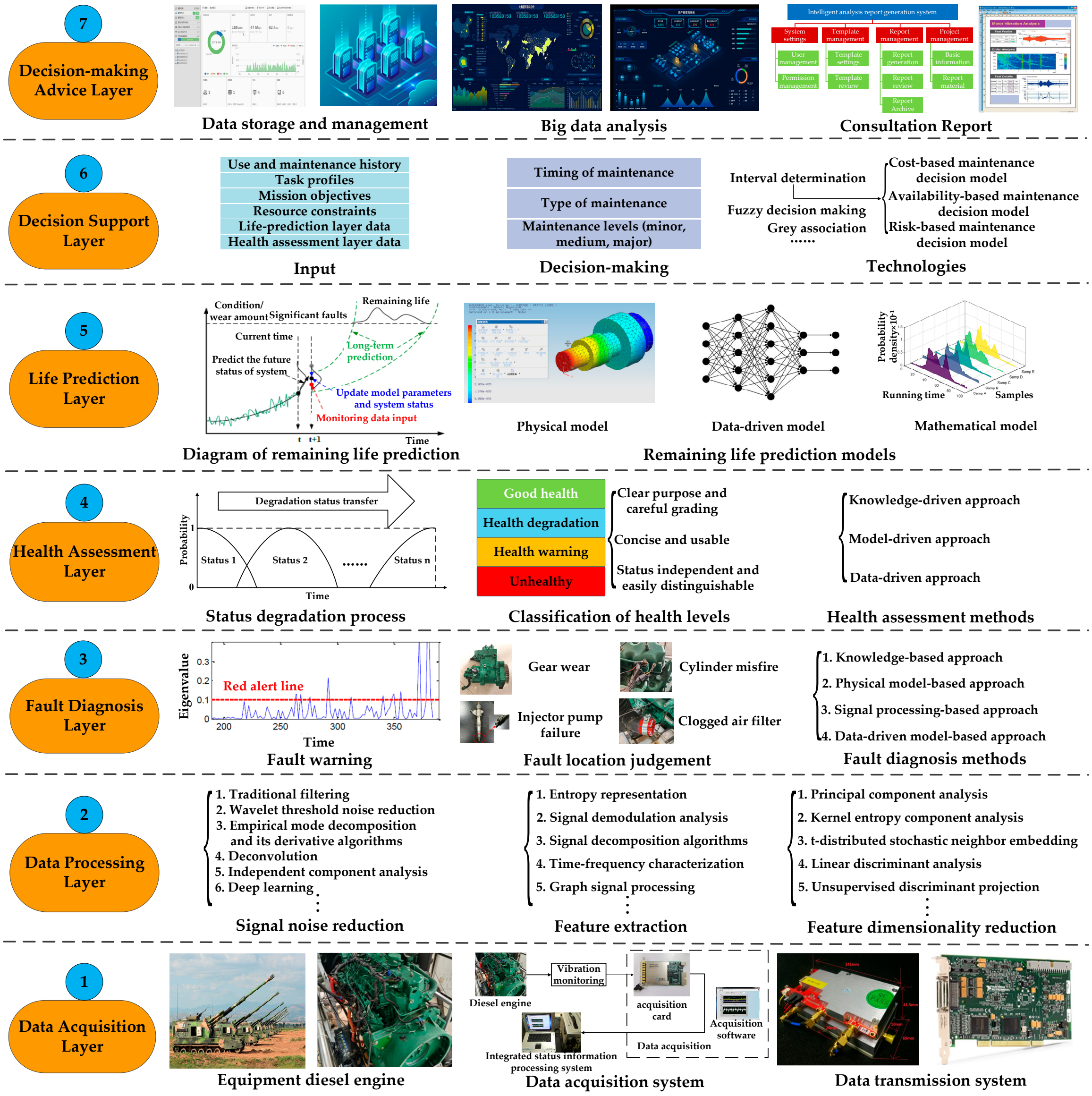


Figure 2. Diesel engine equipment—PHM system architecture.

In summary, the PHM system architecture for diesel engine equipment makes up for the limitations of traditional maintenance support methods and provides a set of theoretical and methodological systems with deep potential for diesel engine maintenance support, which has significant military significance and practical needs for the enrichment and development of diesel engine maintenance support theory and technology.

3. PHM Key Technologies for Diesel Engine Equipment

Relying on the analysis of the decision-making process of PHM for diesel engine equipment in the previous section, combined with the existing prominent technical problems and practical needs in diesel engine maintenance support, according to the research progress and hot topics of diesel engine PHM, this section reviews the current situation of research and hotspots around the first four key technologies of the PHM system architecture for diesel engine equipment in Figure 2. That is, the key technologies of diesel engine operation and maintenance, such as data acquisition, data processing, fault diagnosis, and health status assessment, are discussed.

3.1. Data Acquisition

The acquisition of condition monitoring data is the basis for fault diagnosis and health status assessments of diesel engines. With the development of testing technology, the techniques that can be applied to obtain data reflecting the operating condition of diesel engines are vibration signal, sound signal, infrared thermography, oil analysis, etc.

Diesel engines have a complex working environment (affected by high temperature, high pressure, and a harsh environment), and the whole engine body will vibrate under the combined force of various components during the working process. The path of the diesel engine vibration excitation is shown in Figure 3. The vibration signal is easy to collect, simple, and feasible without disassembling the body of the diesel engine, etc. It can quickly reflect the health status of the equipment and is suitable for online or offline condition monitoring. The installation position of the vibration sensors (#1 to #6) when collecting the diesel engine vibration signal is shown in Figure 4. Therefore, the vibration signal-based diesel engine condition monitoring data acquisition method has become a hot spot for research. Jiang et al. [4] proposed a diesel engine valve clearance fault diagnosis method based on the Teager energy operator (TEO) gradient neighborhood vibration shock start point adaptive accurate extraction. Cai et al. [5] discussed a fault identification method for visualizing diesel engine vibration signals based on an improved local binary model with two-way two-dimensional principal component analysis.

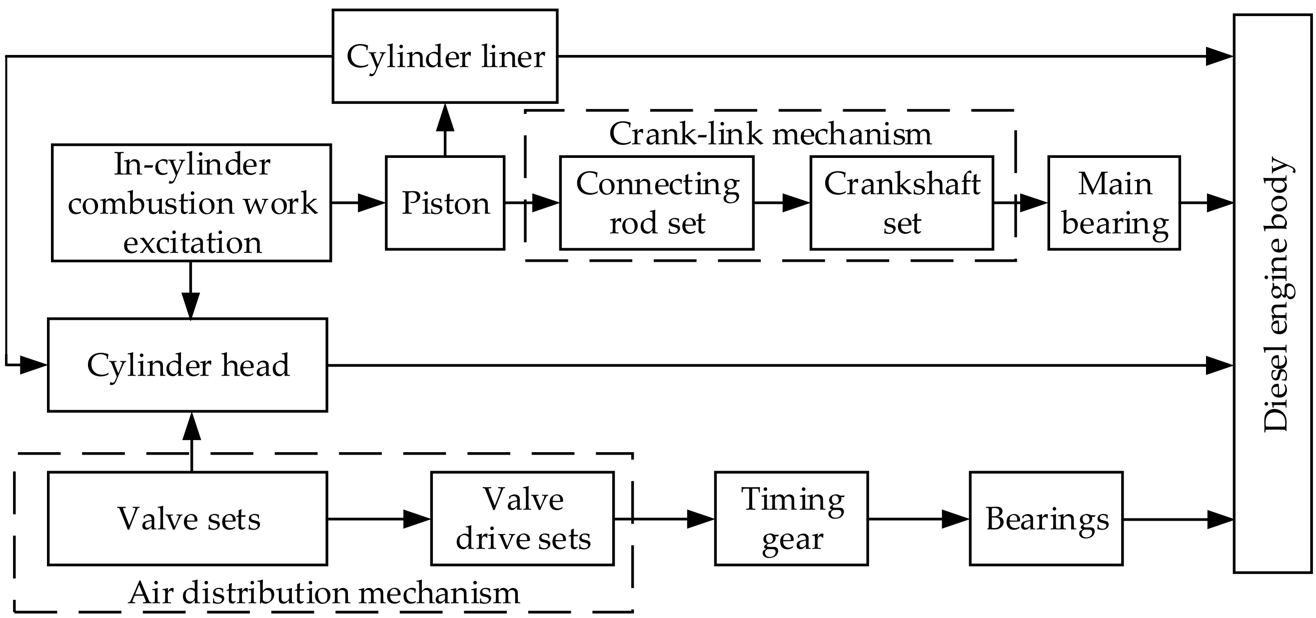
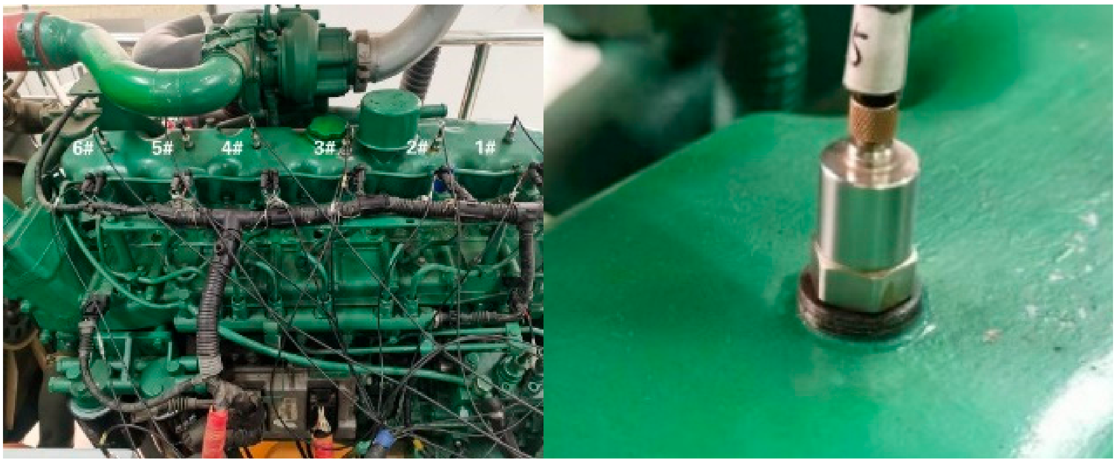


Figure 3. Diesel engine vibration excitation diagram.

Acoustic emission technology is a non-destructive monitoring technique developed in recent years that uses acoustic emission sensors to non-destructively monitor the sound emitted during the operation of diesel engines. Yan et al. [6] constructed a diesel engine acoustic fault diagnosis method based on variational mode decomposition (VMD), Mel-frequency cepstral coefficient (MFCC), and a long short-term memory (LSTM) network. Ibarra-Zarate et al. [7] used the cepstral pre-whitening technique to analyze equipment fault vibration signals and acoustic emission signals, and the results showed that the diagnostic results based on vibration signals outperformed those of acoustic emission signals. Acoustic emission fault characteristic frequencies are usually much higher than vibration characteristic frequencies, requiring very high sampling frequencies and consuming large amounts of computer memory.



(**a**) (**b**)

Figure 4. Mounting position of vibration sensors: (**a**) sensors mounting position and (**b**) diagram of sensors installation.

Based on the principle that the increase in stress at the failure location of diesel engines causes a rise in temperature, the infrared thermal camera is used to collect infrared thermal images of the diesel engine and assess the operating status of the diesel engine by observing the temperature distribution in the thermal images, which has the advantages of being non-contact and requiring no downtime. Wang et al. [8] reviewed the current status of research on diesel engine fault diagnosis based on infrared thermal images and proposed the process of diesel engine fault diagnosis based on thermal images. He et al. [9] studied a diesel engine fault diagnosis method based on small sample thermal images with an augmented convolutional neural network (CNN). Compared with vibration signals, thermal image data storage requires a large amount of computer memory, and although it can diagnose the location of faults, it is difficult to determine the type of fault. At present, thermal imaging technology is mainly used in the fault detection of electronic products and is still in the exploration stage in the field of diesel engine fault diagnosis.

Oil analysis technology uses online monitoring sensors to analyze the wear particle characteristics (size, quantity, generation rate, etc.) and metal composition of diesel engine lubricating oil samples to indirectly determine the wear of metal components and thus the operating condition of the diesel engine. Yan et al. [10] investigated weighted evidence data fusion techniques to enable fault diagnosis of diesel engine drive systems by monitoring lube oil fluid information. Liu et al. [11] proposed an intelligent monitoring technique for engine lubricating oil based on kinematic analysis of microfluidic oil wear particles and developed a real-time tracking condition monitoring algorithm. Compared to vibration analysis, the oil collection process is complex, and the analysis steps are tedious and time-consuming, making it more suitable for detecting the extent of the fault, while determining the exact location of the fault is relatively difficult.

Considering the operability of diesel engine condition information acquisition, the theoretical basis of signal analysis, and the accuracy of fault diagnosis, vibration signals have more advantages compared with other data acquisition techniques. The acquisition of signals reflecting the operating condition of the diesel engine through vibration sensors is simple, diagnostically accurate, efficient, and easy to apply in engineering. The subsequent content is based on vibration signals.

3.2. Data Processing

The raw signals reflecting the operating conditions of diesel engines are usually of poor quality and require effective data processing methods to guarantee data quality and extract reasonable feature parameters. This sub-section discusses key data processing techniques such as vibration signal noise reduction, fault feature extraction, and feature dimensionality reduction.

3.2.1. Vibration Signal Noise Reduction

Fault components in diesel engine vibration signals can be enhanced through noise reduction processing. Common methods that can be applied to diesel engine vibration signal noise reduction include conventional filtering, morphological filtering, singular value decomposition (SVD), wavelet threshold noise reduction, empirical mode decomposition (EMD) and its derivatives, deconvolution, independent component analysis (ICA), deep learning, etc.

Filtering techniques are widely used in the field of vibration signal noise reduction because they are simple and easy to implement. Diesel engine vibration signals contain various frequency components, some of which may have the same interference frequencies as the characteristic frequencies, so traditional linear filtering methods such as low-pass, high-pass, and band-pass are not effective in filtering out the noise in the signal. Li et al. [12] investigated a noise reduction method based on interval local mean decomposition (LMD) with parabolic tracking time-frequency peak filtering (PTTFPF) and verified experimentally that the noise reduction performance of this method is better than that of conventional Kalman filtering. To address the problem that the modulation signal bi-spectrum (MSB) is susceptible to non-Gaussian noise in engineering applications, Guo et al. [13] constructed an autoregressive modeling filter based on non-Gaussian noise suppression to filter out non-Gaussian noise from the MSB processed signal. Time synchronous averaging (TSA) is essentially a series of equidistantly distributed bandpass filters. To solve the problem that TSA mixes octave signal waveforms at specific frequencies, leading to difficult decomposition, Guo et al. [14] proposed an improved TSA noise reduction method based on correlation detection, without the need to obtain the exact period of the vibration signal and without strict requirements on the smoothness of the signal.

Morphological filtering is a non-linear filtering technique developed from mathematical morphological theory. Duan et al. [15] designed adaptive morphological filters to address the problem that the filtering effect of conventional morphological operators is susceptible to random pulses. Yan [16] proposed a noise suppression method based on adaptive smooth continuous-scale morphological filtering of partial differential equations. Although morphological filtering has achieved good results in the field of vibration signal noise reduction, both how to construct a suitable filter in this method and the problems of waveform distortion in the filtering process need further research.

SVD is a non-linear filtering technique whose singular values can reflect the proportion of true and noisy components of the signal and has been widely used in the field of vibration signal noise reduction. Liang et al. [17] used the mean descent rate factor to construct a singular value descent rate difference spectrum and used the maximum value of this spectrum as the singular value threshold to design a mean descent rate-based noise reduction method for SVD vibration signals. In response to the deficiency that the noise reduction effect of the SVD method depends on the selection of effective singular values, Zhao et al. [18] proposed the concept of singular value difference spectrum for describing the sudden change state of complex signal singular values, and the automatic selection of effective singular values can be achieved by the peak of the difference spectrum.

Wavelet thresholding noise reduction includes soft thresholding and hard thresholding noise reduction methods, which have the advantages of small computational effort and wide application. However, there are deviations between the wavelet coefficients after soft thresholding and the true wavelet coefficients, which result in large errors when reconstructing the signal. The hard thresholding function is discontinuous and may generate oscillations after noise reduction. In addition, the selection of a suitable wavelet basis function requires a certain degree of a priori knowledge of the signal itself, making the method less adaptive. Zhang et al. [19] proposed a noise reduction method for vibration signals based on the modified dual-tree complex wavelet transform (DTCWT), which adaptively determines the number of decomposition levels and effective sub-bands of the DTCWT based on the correlation coefficient matrix. Ying et al. [20] studied wavelets from the perspective of real-time, solved the problem of constructing real-time wavelet noise reduction systems for engineering applications, and validated the method with the collected diesel engine vibration signals.

Based on wavelet noise reduction, scholars have proposed adaptive noise reduction methods for vibration signals, such as EMD and its derivative algorithms. Sha et al. [21] proposed a noise reduction method based on differential EMD and polar field mean mode decomposition. However, EMD suffers from endpoint effects, mode mixing, and other problems. The empirical wavelet transform (EWT) uses wavelet analysis as a framework and combines the adaptive nature of EMD. Chen et al. [22] proposed a noise reduction method based on improved EWT with compression sensing (CS), but the robustness of the method is poor. LMD has greatly improved over EMD in terms of reducing the number of iterations and suppressing endpoint effects. Ning et al. [23] studied a hybrid noise reduction method based on LMD, sample entropy, and time-frequency peak filtering. However, LMD suffers from the problem of mode mixing, and the decomposition results are prone to bias. The ensemble empirical mode decomposition (EEMD) improves the mode mixing problem in EMD, but the computational efficiency of the method is low. Guo et al. [24] proposed a multi-stage noise reduction method based on EEMD, wavelet thresholding, and MSB that can remove the interference components from the strong background noise vibration signal. To improve the low reconstruction accuracy of EEMD, Niu et al. [25] proposed a vibration signal noise reduction method based on complementary ensemble empirical mode decomposition (CEEMD) and bilateral filtering. Considering that statistical metrics such as correlation coefficient and kurtosis are invalid when containing non-Gaussian noise, Zhou et al. [26] proposed a noise reduction method combining complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) and a noise quantization strategy. The intrinsic time-scale decomposition (ITD) method has good time-frequency aggregation. Gao et al. [27] proposed a noise reduction model combining ITD with adaptive maximum correlation kurtosis deconvolution. Compared with the above methods, VMD has been favored by scholars since its proposal for its good noise robustness, low computational complexity, and complete mathematical theoretical foundation. Dai [28] introduced time-frequency streamline learning in the adaptive VMD, which effectively suppressed the noise in the vibration signal.

Deconvolution recovers the fault shock characteristics from the signal without manual pre-setting of the basic functions and is suitable for processing non-linear and non-smooth vibration signals. Zhou [29] proposed a vibration signal noise reduction method based on adaptive maximum cyclic smoothness blind deconvolution. Meng et al. [30] used an autoregressive moving average model to remove intrinsic components and pre-whitened signals, and then recovered the periodic fault signals by adaptive multipoint optimal minimum entropy deconvolution to achieve secondary noise reduction of the vibration signals. However, the deconvolution method is prone to generating pseudo-pulse sequences if the length of the filter is not chosen properly.

ICA is based on the theory of sample higher-order statistical analysis and has a strong blind discrimination capability, which can extract the true components of the mixed signal and has a better noise reduction effect compared with the traditional adaptive filtering method. Li et al. [31] proposed a vibration signal noise reduction method based on cross-spectral analysis of CEEMDAN combined with ICA, which effectively improved the signal-to-noise ratio (SNR). However, ICA requires the number of sources to be less than or equal to the number of observed signals, which is not suitable for the common underdetermined single channel situation in engineering.

Deep learning methods can extract abstract features from vibration signals and achieve adaptive noise reduction without extensive signal processing knowledge, which is more effective than traditional noise reduction methods. Zhao et al. [32] constructed a deep residual shrinkage network fusing attention mechanisms and soft threshold filtering to achieve adaptive threshold filtering and achieve a better noise reduction effect in the case of strong noise. In response to the lack of noise reduction structure in traditional CNN, Jia et al. [33] proposed an end-to-end CNN model based on Gramian noise reduction. Zhao et al. [34] proposed a vibration signal noise reduction method based on stacked denoising auto-encoder (SDAE), using encoder and decoder to extract features in the signals and reconstruct them, respectively. However, the deep learning method has problems, such as the need to collect vibration signals with distinct features in advance and the need for a large number of samples for training.

3.2.2. Fault Feature Extraction

In the area of fault feature extraction based on vibration signals, scholars have conducted a lot of theoretical research and application exploration. Typical methods that can be applied to diesel engine fault feature extraction include entropy characterization, signal demodulation analysis, signal decomposition algorithms, time-frequency representation, graph signal processing, sparse representation, stochastic resonance (SR), morphological filtering, fractal dimension, genetic programming (GP), deep learning, etc.

Entropy characterization is a non-linear dynamical method that reflects the different levels of failure of equipment by estimating the complexity of the vibration signal and quantitatively reflecting the characteristic information of complex signals. To effectively extract transient pulse signals, Li et al. [35] introduced wavelet packet transformation into band entropy and enhanced the depth of band entropy using adaptive resonant bandwidth and power amplitude spectral entropy optimization. Wang et al. [36] proposed a multichannel fault feature extraction method called variational embedded multiscale diversity entropy. Yang et al. [37] discussed the use of hierarchical multiscale permutation entropy to represent fault characteristics. Wang et al. [38] investigated a highly flexible feature extraction method called concentric diversity entropy, which uses multiple wavelets to extract fault features over the entire frequency band.

Signal demodulation analysis demodulates the signal associated with the fault from the modulated signal to avoid confusion with other disturbances. Common signal demodulation methods include envelope demodulation, energy operator demodulation, and cyclic smooth demodulation.

Envelope demodulation is divided into generalized detector filter demodulation (including high-pass absolute demodulation, detector filter demodulation, and square demodulation) and Hilbert demodulation. Of these, Hilbert demodulation is the most widely used and representative demodulation method, as it enables both amplitude and phase (frequency) demodulation. Wang et al. [39] extended the Hilbert transform to a fractional-order Hilbert transform defined in the frequency domain, where the fault characteristic frequencies can clearly appear in the fractional envelope spectrum. To address the problem that envelope order tracking may be ineffective for multiple pulse sources, Yang et al. [40] proposed a weak fault feature extraction method combining envelope order tracking and constrained ICA.

TEO is a non-linear energy tracking operator that can be used for real-time processing of signals. Compared with Hilbert transform demodulation, this method is able to suppress endpoint effects, highlight signal transient shocks, and have low computational complexity. Han et al. [41] proposed a weak fault feature extraction method fusing TEO and CEEMD. However, TEO demodulation itself has errors and is influenced by noise. The envelope derivative energy operator is based on the envelope derivative operation, which can detect transient changes in the signal and further improve the demodulation performance with lower complexity compared with TEO. Qi et al. [42] proposed an improved envelope derivative energy operator to enhance the fault shock characteristics in morphologically filtered signals. The 1.5-dimensional symmetric differential energy operator solves the problems of low demodulation accuracy and poor noise reduction in 1.5-dimensional TEO. Chen et al. [43] proposed a fault feature extraction method for vibration signals based on optimized singular spectrum decomposition and demodulation of a 1.5-dimensional symmetric differential energy operator.

Diesel engines are mainly in reciprocating motion; the vibration signal collected is usually cyclic smooth, and cyclic smooth demodulation can be applied. Cyclic statistics for cyclic smooth demodulation usually use spectral correlation functions and cyclic autocorrelation functions. However, this method is computationally less efficient compared with Hilbert demodulation [44]. He et al. [45] proposed a logarithmic envelope self-spectrogram vibration signal multi-fault feature extraction method. Yao et al. [46] studied a weak fault feature extraction method for equipment based on dual-window spectral fusion enhancement. The kurtosis diagram is based on spectral kurtosis and avoids the shortcomings of traditional envelope demodulation analysis, which requires empirical selection of frequency bands. Yuan et al. [47] proposed a simultaneous multi-channel vibration signal feature extraction method called Msegram.

The three demodulation methods mentioned above are closely related to each other and can be replaced equivalently in a unified framework. In the case of multi-fault vibration energy imbalance and random shock interference, the optimal fault demodulation band selection is the most critical problem facing the signal demodulation technique and is a task that requires further research.

By decomposing the signal, the useful signal components can be extracted, enabling the separation and extraction of fault features. Yuan et al. [48] proposed a dual-mode noise reconstruction EMD weak fault feature extraction method combining adaptive decomposition and natural noise reduction. Liu et al. [49] studied a fault feature extraction method based on EEMD and curve code CC. Wang et al. [50] used the ratio of the periodic modulation component caused by the fault to the generalized disturbance as a new criterion for CEEMDAN to quantify the degree of fault correlation in vibration signals and were able to successfully extract fault features in the presence of both Gaussian and non-Gaussian noise disturbances. Xu et al. [51] proposed a quaternion EWT multi-channel signal fault feature extraction method that achieved a comprehensive use of data in different directions in space. He et al. [52] proposed a fault feature extraction method based on parametric adaptive optimization of VMD with the fusion impact index of fault components as the objective function. Zhang et al. [53] integrated the logarithmic window energy criterion into multichannel multicomponent decomposition and later applied the method to vibration signal fault feature extraction. Yu et al. [54] proposed a fault feature extraction method based on ITD with sparse coding shrinkage. Cheng et al. [55] improved the symplectic geometry mode decomposition (SGMD) by calculus operators and characteristic value decomposition to improve the characteristic enhancement capability and noise robustness.

Currently, most of the fault feature extraction methods are based on one-dimensional vibration signals, and although the non-linear features of the original signal can be preserved to a certain extent, the correlation of the vibration signals on the time series is not taken into account. In addition, network models are more suitable for extracting feature information from high-dimensional data. As a result, scholars in this field have begun to investigate the conversion of diesel engine 1D vibration signals into 2D images by some method for feature extraction of image data. Shen et al. [56] performed the Gabor transform on the vibration signal to obtain the time-frequency diagram of each operating status of the diesel engine. Mou et al. [57] converted the diesel engine vibration signal into a time-frequency diagram by smoothing the pseudo-Wigner distribution.

Graph signal processing methods are graph structures that study the relationships of vibrating signals. A complex network is a special kind of graph structure that is able to capture the characteristics of non-smooth signals. The viewable algorithm is capable of transforming time-discrete sequences into complex networks. Chen [58] proposed a fault feature extraction method based on viewable mapping amplitude entropy without considering the problem of parameter selection. The ability to link fault signals to other complex network diagrams characterizing the structure of the time series and to extract indicators that better characterize the faults needs further research.

Sparse representation means that as few atoms as possible are selected to represent the signal in the overcomplete dictionary, which is characterized by sparsity and adaptiveness. Li et al. [59] constructed a non-convex penalty function based on the elastic net and Lp criterion and proposed a sparsely enhanced periodic overlapping group contraction method. Yao et al. [60] proposed an adaptive period matching enhanced sparse representation weak fault feature extraction method by embedding period estimation into the sparse representation. However, the sparse coefficients are difficult to solve and construct over-complete dictionaries, and the vibration signals processed by traditional sparse decomposition methods suffer from weak signal fidelity, poor model convexity preservation, and poor model generality.

SR enhances weak fault characteristics in vibration signals by adding noise to the non-linear system. Gong et al. [61] proposed adaptive cascade SR to enhance and extract weak fault features in the presence of strong background noise. Li et al. [62] developed a dual feedback cascaded monostable SR system from the perspective of feedback control and multi-system synergy, which can better match the frequency characteristics of the target signal. However, the quality of the SR output is influenced by a combination of adjustable parameters.

Morphological operators can be divided into two main categories: noise-reducing operators and feature-extraction operators. In feature extraction, morphological filtering can also achieve more satisfactory results. Chen et al. [63] constructed a generalized composite morphological operator framework for improving the extraction of fault transient pulse features. Chen et al. [64] proposed an adaptive time-varying morphological filtering method that can adaptively determine the shape and scale of structural elements based on the inherent characteristics of the vibration signal, effectively improving computational efficiency.

The fractal dimension is the basis of chaos theory and fractal theory and can be used to describe the similarity of the local signal with the overall signal. Yan et al. [65] investigated a fractal dimension method based on composite multiscale morphology to quantify the self-similarity of vibration signals. The detrended fluctuation analysis (DFA) method can describe the irregularity and self-similarity of the signal locally and as a whole and extract the features of the multifractal spectrogram as signal features. Zhao et al. [66] proposed an equipment fault feature extraction method based on improved DFA and linear discriminant analysis.

The GP method automatically generates solutions to problems without the need for domain knowledge and has flexible programmatic expression. Peng et al. [67] discussed automatic GP-based feature extraction and construction methods. Peng et al. [68] proposed a GP multi-view feature construction and integration method to automatically construct low-level features from different views into high-level features to improve the diversity and discrimination of fault features. However, the GP method has problems with the need to set up individual fitness evaluation processes, program structures, sets of functions, sets of terminators, etc.

Deep learning can extract valuable fault characteristic information from data reflecting the operational status of equipment. Zhao et al. [69] proposed a fault feature extraction method based on semi-supervised deep sparse self-coding based on a sparse self-coding model. Yu et al. [70] constructed a one-dimensional residual convolutional self-coding model to learn features directly from vibration signals in an unsupervised learning manner. Zhang et al. [71] designed a compact enhanced multi-scale CNN feature extraction model that can extract features at different time scales without adding convolutional layers and alleviate the overfitting problem caused by complex networks.

3.2.3. Feature Dimensionality Reduction

The high-dimensional complex fault features of the extracted equipment diesel engine may produce redundancy, which not only affects diagnostic accuracy but also reduces computing efficiency. Therefore, compressing the data by feature dimensionality reduction on the basis of keeping the original features of the data as much as possible is the key to improving diagnostic efficiency.

The methods that can be applied to the dimensionality reduction of diesel engine faults are divided into linear and non-linear dimensionality reduction methods (non-linear dimensionality reduction is also divided into kernel function-based and characteristic value-based methods). Linear dimensionality reduction methods include principal component analysis (PCA), ICA, linear discriminant analysis (LDA), etc. Non-linear dimensionality reduction methods based on kernel functions include kernel principal component analysis (KPCA), kernel entropy component analysis (KECA), kernel independent component analysis (KICA), etc. Non-linear dimensionality reduction methods based on characteristic values (stream learning) include: t-distributed stochastic neighbor embedding (t-SNE), isometric mapping (Isomap), locally linear embedding (LLE), orthogonal locality preserving projections (OLPP), local fisher discriminant analysis (LFDA), neighborhood preserving embedding (NPE), unsupervised discriminant projection (UDP), local tangent spatial algorithm (LTSA), multi-dimensional scaling (MDS), maximum variance unfolding (MVU), etc. On this basis, Chen et al. [72] proposed a feature dimensionality reduction method based on sparse discriminative stream projection, which can effectively extract the valuable low-dimensional intrinsic features hidden in the high-dimensional feature dataset. Wang et al. [73] proposed a low-dimensional, sensitive fault feature extraction method integrating KPCA and t-SNE, which can take into account both local and global structural features of the sample data. Qi et al. [74] used a uniform stream shape approximation and projection algorithm with a supervised type of Mahalanobis distance for dimensional approximate reduction to obtain low-dimensional and sensitive fault features.

3.3. Fault Diagnosis

Most of the existing research results on the fault diagnosis of diesel engine equipment has studied the fault diagnosis method by pre-setting the fuel supply system fault of the diesel engine. As can be seen from the fault statistics of a type of self-propelled artillery diesel engine shown in Figure 5, the fuel supply system fault has the highest probability of occurring in the actual use of the diesel engine, reaching 27.0%. As shown in Figure 6, in the process of pre-setting the fault, the cylinder can be pre-set by disconnecting the cylinder ignition power line to pre-set the cylinder misfire fault, adding the air intake outer cover to pre-set the air filter blockage fault, replacing the injection pump fault parts to pre-set the injection pump fault leading to insufficient fuel supply (the internal gear of the injection pump wears out leading to low fuel supply pressure), and replacing the injector fault parts (the injector needle valve wears out) to pre-set the injector drip fault.

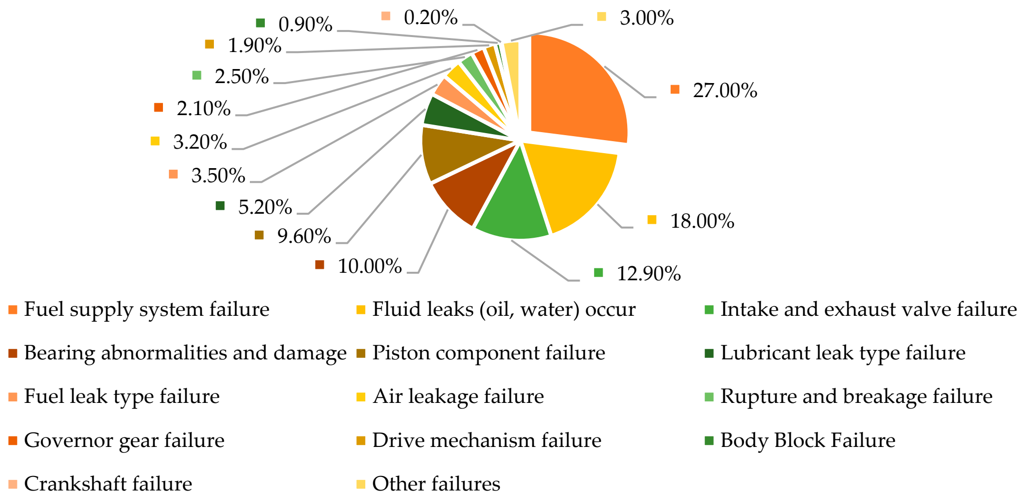


Figure 5. Statistical chart of diesel engine faults for a certain type of self-propelled artillery.

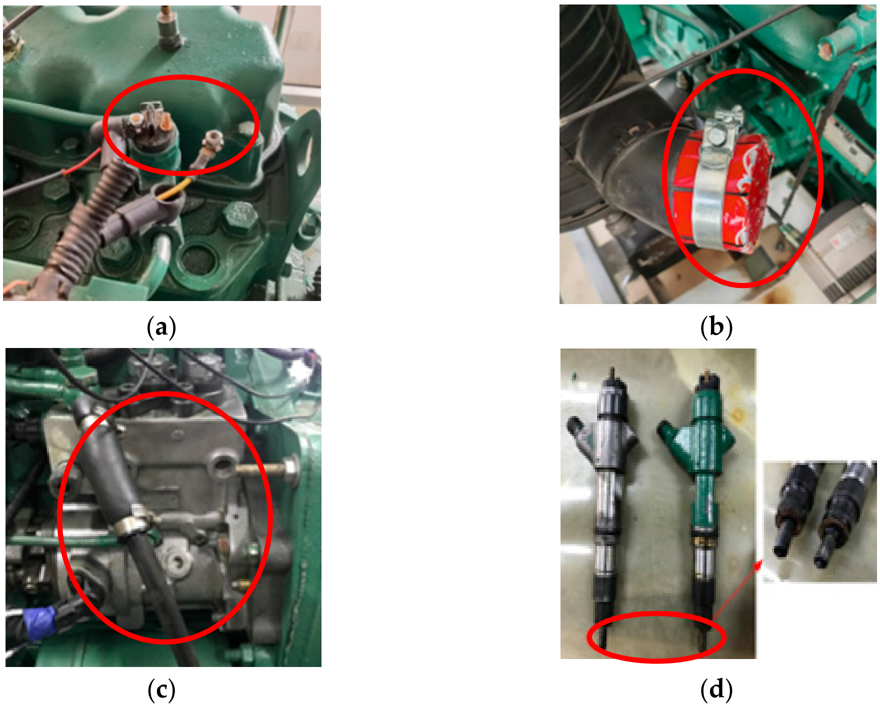


Figure 6. Diesel engine pre-set faults: (**a**) disconnect the ignition power cable; (**b**) add an air intake cover; (**c**) replace the faulty injection pump; and (**d**) replace the faulty injector.

The equipment diesel engine fault diagnosis methods include knowledge-based, model parsing-based, signal processing-based, and machine learning-based methods. Among them, the machine-learning based methods can be further divided into classical machine learning and deep learning. A summary of each method is shown in Table 1.

Table 1. Characteristics of fault diagnosis methods.

Methods	Model Complexity	Is It Necessary to Prior Check the Physical Mechanism of the Diesel Engine	Accuracy	Generalizability	Amount of Knowledge/Data Required
Knowledge-based method	Low	Yes	Medium	Poor	Large
Model parsing-based method	High	Yes	Medium	Poor	Low
Signal processing-based method	Low	No	High	Medium	Medium
Machine learning-based method	Medium	No	High	Strong	Large

Knowledge-based methods use empirical data or expert experience fused with computer science to create expert systems for knowledge-based diagnostic reasoning, which play an important role in early fault diagnosis. Xu et al. [75] constructed an expert system for diesel engine fault diagnosis based on belief rules. Kang et al. [76] designed a hierarchical fault detection and diagnosis method that incorporates diesel engine domain knowledge with advanced data analysis techniques. To obtain the entities needed to build a knowledge graph from diesel engine fault diagnosis texts, Zhong et al. [77] proposed a Chinese named entity recognition method that introduces a word-set-level attention mechanism, overcoming the shortcomings of the traditional method that ignores the different importance of individual word sets. Chen [78] proposed a relationship extraction method fusing a multiscale attention mechanism with a BERT model and a non-local convolutional embedding knowledge map complementation technique for obtaining the relationships needed to build a knowledge map from diesel engine fault diagnosis texts as well as solving the problem of incomplete fault knowledge maps, respectively. However, knowledge-based methods lack the ability to self-learn, are more dependent on experience and knowledge, are difficult to extend and correct, and are more complex to implement. Often, experience and knowledge are difficult to obtain, and incomplete or incorrect experience and knowledge lead to low fault diagnosis accuracy.

The model-parsing-based method is applicable to component-level equipment and requires modeling between fault data and fault types. Zhong et al. [79] proposed a sparse kernel local Fisher discriminant analysis method to improve the performance and interpretability of diesel engine fault diagnosis models. Considering the variable load and compact structure of diesel engines, Wang et al. [80] established a mapping model between the mean value of shaft radial vibration and misalignment value based on the shaft shape characteristics and proposed a quantitative misalignment detection method based on this model. To address the problem that centralized methods make it difficult to detect faults in large-scale dynamic processes, Zhong et al. [81] proposed a distributed diesel engine fault detection model based on variable chunking with Bayesian inference. Considering that it is more difficult for a single supervised or unsupervised method to combine the information of labeled and unlabeled samples, Zhong [82] constructed a semi-supervised learning-based fault detection and diagnosis model for diesel engines. Ma [83] built a simulation model of diesel engine piston motion, analyzed the radial motion pattern of the piston in the cylinder and the rotation characteristics around the piston pin axis, and studied the effect of cylinder clearance on the piston knocking force. However, building the model requires an in-depth understanding of the fault and failure mechanisms of diesel engines and a comprehensive consideration of the physical and chemical processes to which the components are subjected, resulting in a more difficult modeling process that is not applicable to system-level equipment and is less versatile.

Signal processing-based methods use signal processing techniques to process fault signals to obtain different statistical features in the time domain, frequency domain, and time-frequency domain for effective fault diagnosis. Such methods overcome the difficulties of mathematical modeling and are widely used in the field of diesel engine fault diagnosis. Ke et al. [84] proposed a method for identifying the type and degree of diesel fuel injector faults based on multi-scale bidirectional diversity entropy. Tang [85] studied a diesel engine fault diagnosis method based on VMD with kernel fuzzy C-mean clustering. Zhang et al. [86] used the fourth-order accumulation of reconstructed signals from two stages of VMD and robust ICA decomposition results as fault determination indicators and used the Euclidean distance between each condition point and the injection fault clustering center to distinguish the fault types of diesel engines. Cai [87] discussed a time-frequency analysis method based on threshold filtering VMD and Margenau–Hill time-frequency distribution (MHD) for processing vibration signals, extracting time-frequency map features using local non-negative matrix factorization (NMF), and implementing diesel engine fault diagnosis by improving the particle swarm optimization (PSO) support vector machine (SVM) model. Jiang et al. [88] studied a fault diagnosis method for diesel engines based on wavelet packet energy spectrum feature extraction and fuzzy entropy feature selection. However, such methods require strong expertise and signal processing tools, and the extracted features may cause loss or redundancy of the original information. In most cases, fault features also need to be filtered, evaluated, and fused, and the process often has no unified quantitative indicators, relying only on certain manual experience or mathematical and statistical methods. There is a problem of losing some of the feature information, resulting in an unsatisfactory diagnosis.

With the rapid development of artificial intelligence technology, machine learning-based methods are the mainstream direction of current research. The method uses different types of sensors to collect signals that can characterize the working status of a diesel engine and applies different feature extraction methods and pattern recognition techniques to identify its fault types.

Classical machine learning methods rely on the manual extraction of features from diesel engine vibration signals and use the extracted features to train machine learning models that can automatically identify fault types. These methods can establish a direct relationship between fault types and features based on data, mainly including SVM, extreme learning machine (ELM), probabilistic graphical model (PGM), Bayesian network (BN), error back propagation training (BP), probabilistic neural network (PNN), decision tree (DT), and K-nearest neighbor (K-NN) models. Some common features of signal statistics are listed in Table 2. In Table 2, $x_{\mathrm{i}}(i = 1, 2, \ldots, N)$ represents the i-th sample point of a signal of length N. $x_{\max}$ represents the maximum value of the signal. $x_{\min}$ represents the minimum value of the signal. $x_{\mathrm{p-p}}$ represents the peak-to-peak value of the signal. $\overline{x}$ indicates the average value of the signal. $\overline{x}_{\mathrm{abs}}$ represents the absolute mean value of the signal. σ^2 represents the variance of the signal. σ represents the standard deviation of the signal. x_{rms} denotes the root mean square of the signal. x_{ske} represents the skewness of the signal. x_{kur} represents the kurtosis of the signal. S_{f} represents the waveform factor of the signal. C_{f} represents the impulse factor of the signal. I_{p} represents the peak factor of the signal. C_{e} represents the clearance factor of the signal.

Table 2. Commonly used statistical features of signals.

Serial Number	Feature Parameters	Calculation Formula	Serial Number	Feature Parameters	Calculation Formula
1	Maximum value	$x_{\max} = \max(x_{\mathrm{i}})$	8	Root mean square	$x_{\mathrm{rms}} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_{\mathrm{i}}^2}$
2	Minimum value	$x_{\min} = \min(x_{\mathrm{i}})$	9	Skewness	$x_{\mathrm{ske}} = \frac{1}{N}\sum_{i=1}^{N} x_i^3$
3	Peak-to-peak value	$x_{\mathrm{p-p}} = x_{\max} - x_{\min}$	10	Kurtosis	$x_{\mathrm{kur}} = \frac{1}{N}\sum_{i=1}^{N} x_i^4$
4	Average value	$\overline{x} = \frac{1}{N}\sum_{i=1}^{N} x_{\mathrm{i}}$	11	Waveform factor	$S_{\mathrm{f}} = x_{\mathrm{rms}}/\overline{x}_{\mathrm{abs}}$
5	Absolute average	$\overline{x}_{\mathrm{abs}} = \frac{1}{N}\sum_{i=1}^{N} \lvert x_i \rvert$	12	Impulse factor	$C_{\mathrm{f}} = x_{\max}/\overline{x}_{\mathrm{abs}}$
6	Variance	$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N} (x_{\mathrm{i}} - \overline{x})^2$	13	Peak factor	$I_{\mathrm{p}} = x_{\max}/x_{\mathrm{rms}}$
7	Standard deviation	$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (x_{\mathrm{i}} - \overline{x})^2}$	14	Clearance factor	$C_{\mathrm{e}} = x_{\max}/\left(\frac{1}{N}\sum_{i=1}^{N} \sqrt{\lvert x_i \rvert}\right)^2$

Lu et al. [89] proposed a restricted Boltzmann ELM-based fault diagnosis model for diesel engines by constructing feature mappings to recursively adjust the weights between input neurons and hidden neurons. Yang et al. [90] discussed a fused discriminative NMF and KNN approach for diesel engine fault diagnosis. Cai et al. [91] studied a diesel engine fault diagnosis method based on a rule-based algorithm combined with a BN or BP. To solve the problem of poor fault tolerance in a single model, Xu et al. [92] fused an improved evidence inference rule model, a belief rule base inference model, and an artificial neural network model in the decision layer, proposed a multi-classifier fusion method for diesel engine wear fault diagnosis, and optimized the weights of each model by a genetic algorithm (GA). Zhao et al. [93] applied pairwise extended least squares (LS) SVM to diesel engine fault diagnosis, which has the advantage of low model complexity and high generalization capability. Wang et al. [94] constructed a graph convolutional network based on distance and a probabilistic topological graph model to solve the problem of unbalanced classification in diesel engine fault diagnosis. Hou et al. [95] proposed a diesel engine cylinder fault diagnosis model based on an improved GA with a multilayer perceptron (MLP).

Currently, there are few methods based on knowledge and model parsing in diesel engine fault diagnosis research. Methods based on signal processing and classical machine learning face the problem that manual feature extraction is prone to redundancy or loss of raw information and cannot adequately fit the characteristics of industrial big data, which may result in reduced diagnostic accuracy. Shallow classical machine learning models have limited ability to learn to characterize non-linear equipment monitoring data. With the development of industrial big data, the ability of such methods to handle massive amounts of data is clearly inadequate.

Deep learning is a branch of machine learning that has become the most researched area for diesel engine fault diagnosis due to its end-to-end nature and its ability to handle big data. The main methods include deep belief networks (DBN), CNN, auto-encoding (AE), recurrent neural networks (RNN), capsule networks (CN), generative adversarial networks (GAN), etc. Liu et al. [96] constructed a deep neural network consisting of stacked sparse self-encoder (SSAE) and Softmax classification layers for diesel engine fault diagnosis. Jiang et al. [97] proposed a digital twin-assisted diesel engine fault diagnosis method based on adaptive sparse attention networks by embedding soft threshold filtering into the attention layer. Huang et al. [98] proposed a model for diesel engine operating condition identification based on graph attention networks (GAT). Bi [99] designed a DBN-based multi-sample classifier. Li [100] revealed how CNNs work in the field of fault diagnosis, explaining CNNs in principle in terms of class activation graphs and feature visualization. Gao et al. [101] proposed a CNN-based misfire diagnosis method for diesel engines and constructed a real-time fault diagnosis system based on an STM32 microcontroller. Zhang et al. [102] proposed an improved CNN for diesel engine fault diagnosis using exponential linear units as the activation function and global average pooling instead of a fully connected layer, which can still maintain high recognition accuracy when dealing with small sample data. Wang et al. [103] integrated multiple single CNNs to form a new network architecture and proposed a random CNN-based diesel engine fault diagnosis method to fuse the diagnosis results of each model using Dempster synthesis rules. To solve the problem of unsatisfactory diagnosis when different timing fault characteristics of diesel engines are unstable, Feng [104] proposed a fault diagnosis model combining CNN and bi-directional LSTM. Zhang [105] constructed a multi-feature extraction attention mechanism convolutional RNN diesel engine valve clearance anomaly fault diagnosis model and used Bayesian optimization to optimize the hyperparameters in the model. Zhang et al. [106] built a diesel engine fault diagnosis model based on an attention model to optimize the bi-directional gating cycle unit.

The advantages and disadvantages of typical deep learning models are summarized in Table 3, and the basic unit schematic is shown in Figure 7. Different deep learning models have different structures and characteristics, but they are all suitable for situations with large amounts of data and more complex tasks. Some models also have their own unique roles, for example, AE is suitable for extracting features, generating data, and noise reduction, RNN is good at processing time-series data; and GAN is suitable for semi-supervised, unsupervised generative tasks.

Table 3. Characteristics of deep learning models.

Methods	Features	Advantages	Disadvantages
CNN	Processes data with grid-like topology better; weight sharing; supervised learning.	Strong feature extraction capability and fewer parameters.	Complex structure and large amount of data required.
DBN	Multiple restricted Boltzmann machine layers stacked; layer-by-layer greedy learning training model; unsupervised pre-training, supervised fine-tuning model.	Greedy training style and inference easy to handle.	Time consuming training.

Table 3. *Cont.*

Methods	Features	Advantages	Disadvantages
RNN	Includes feedback loops to preserve information from previous units; suitable for time series processing.	Variable input length and strong modelling capability for time-series data.	Prone to gradient loss or explosion problems.
GAN	Consists of a discriminator and a generator; the generator learns the distribution of the input and creates fake data; and the discriminator is used to accept both real and fake data and to identify the authenticity of the data.	No deterministic bias was introduced; generative model; and no Markov chain is required.	Unstable training; need to reach Nash equilibrium.
AE	Consists of an encoder and decoder; reconfigurable input data; unsupervised learning.	Input data does not need to be labelled and is more robust against noise.	Pre-training is required and training may cause a gradient explosion.
CN	Addresses some of the shortcomings of CNNs; capsules are the various features of a particular entity.	Information such as posture and position of features can be saved.	Large calculation volume.

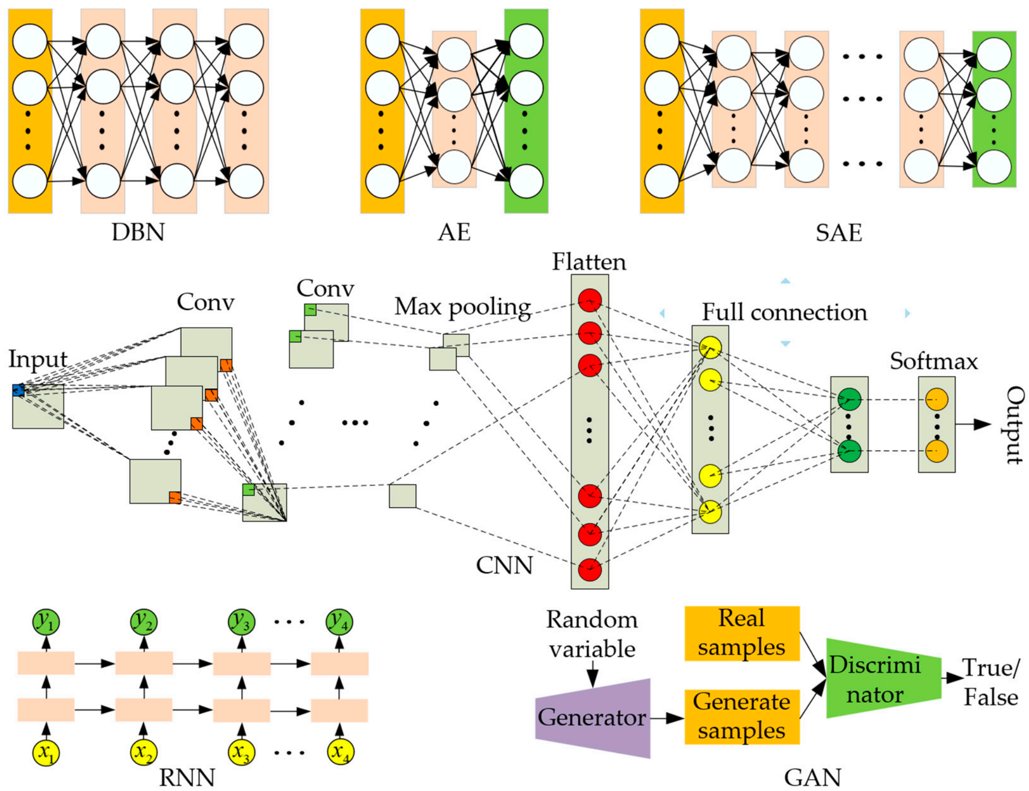


Figure 7. Schematic diagram of the basic unit of typical deep learning models.

However, the application of deep learning models to the fault diagnosis of equipment powered by diesel engines still faces many challenges:

1. Deep learning models usually assume that the training data and the test data in the deployment scenario follow independent, identical distributions. However, the complex and variable operating conditions of diesel engine operation, such as speed and load, often cause a drift in the distribution between training and test data, which limits the diagnostic accuracy of deep learning models;
2. Equipment diesel engine structure is complex; fault parts have a long transmission path from the sensor installation location; fault signals often exhibit complex failure modes, a low signal-to-noise ratio, and non-smooth characteristics; a single

deep learning model faces the problem of a single structure and insufficient feature extraction capability;
3. The deep learning model is a black box model; its internal mechanisms are not clear, and it is not possible to give a basis for its judgment in engineering applications. The model has a large number of hyperparameters; different settings have different effects; and the number of hyperparameter combinations is exponential, making it difficult to optimize the model.

Combining the research of scholars, the main approaches to solving the above problems can be summarized as follows:

1. Signal preprocessing can be used to reduce the drift of the data distribution due to changes in operating conditions. Using transfer learning methods, mainly including domain adaptation and pre-training-trimming strategies, diagnostic knowledge from known conditions is transferred to the target condition to reduce the interference of condition changes with the model. A deep learning fault diagnosis model with robust and generalized condition variation will be investigated;
2. The research is based on a deep integration learning approach to fault diagnosis, where multiple learning units are constructed and integrated with certain strategies to complete the learning task, with the aim of "learning from all sides";
3. Reveal the internal principles of deep learning models and study their automated design and optimization methods.

It is a challenge for machine learning that existing models do not adapt well to new domains under conditions such as small sample sizes and changing work conditions. Transfer learning can learn common features in different but related domains. The main methods include feature transfer, parameter transfer, and domain adaptation, and a summary of each method is shown in Table 4. Zhao et al. [107] constructed a two-stage transfer learning ELM diesel engine fault diagnosis model to achieve individual adaptation to the target domain. Xiong et al. [108] proposed a variable operating condition identification method for diesel engines based on stacked auto-encoders and feature transfer learning. Bai et al. [109] proposed a diesel engine fault detection method based on optimized VMD and ResNet18 transfer learning models. Xu [110] mapped the source and target domain feature sets for different operating conditions of diesel engines using a joint geometric space and statistical distribution alignment transfer learning algorithm. Zhao [111] proposed a transfer model based on the ResNet50 neural network, deep adaptation network, and domain adaptation for diesel engine misfire and valve clearance fault diagnosis under different operating conditions, respectively. Jia [112] conducted an experiment on diesel engine fault diagnosis based on the VGG16 transfer learning CNN structure. However, transfer learning models at this stage still require large amounts of data for training, and their performance is poor when the working conditions vary greatly. Although transfer learning can effectively address the problem of domain distribution drift, it still requires obtaining data from a specific target domain, which has limitations in engineering applications.

Table 4. Characteristics of each transfer learning method.

Methods	Features	Advantages	Disadvantages
Feature transfer	Measure feature mapping by finding a transfer function that connects the source and target domains and complete the transfer from the source to the target domain by learning the feature mapping.	Feature domain adaptation still achieves good results when there are large differences between domains.	Finding the right feature metric between domains is difficult, and the workload is relatively high.

Table 4. *Cont.*

Methods	Features	Advantages	Disadvantages
Parameter transfer	Focuses on tuning discrete models, training model parameters in the source domain, and fine-tuning parameters in the target domain.	Simple method, easy to use, and relatively short training time.	When the difference between the source and target domain segments is greater, the performance is worse, requiring a small portion of the target domain data to be labeled.
Domain adaptive	The problem of variable working conditions is solved by optimizing the distribution of the domain.	Unsupervised or semi-supervised learning, without the need for large amounts of labeled data to complete the transfer.	-

3.4. Health Status Assessment

The diesel engine health status is a discrete status determined by simulating the health of the human body from a bionic perspective, i.e., the reliability and functional performance of the diesel engine during the degradation of its performance. The health status assessment is based on the results of data processing, using failure models or intelligent algorithms to assess the operational status of the diesel engine.

Diesel engine health status assessment can be broadly divided into knowledge-driven, model-driven, and data-driven methods. Wang et al. [113] designed a method for assessing the health status of complex equipment based on rough set theory and evidence theory. Ding [114] used the fuzzy set value statistics method and the entropy weight method to determine the subjective and objective weights of the assessment indexes, respectively, and proposed a diesel engine health status assessment method based on the cloud gravity judgment method. Liang et al. [115] proposed a bi-directional optimization method for health status assessment and maintenance decision-making of electromechanical systems based on the bi-directional integration of health status assessment and maintenance scheduling binary knowledge. Wei [116] discussed the principles of diesel engine health class classification and health status assessment index selection methods and proposed a single-cylinder diesel engine health status assessment method based on the improved gray clustering method and entropy weight method, a diesel engine whole engine health status assessment method based on the cloud gravity judgment method and combined weight method, and a diesel engine whole engine health status assessment method based on D-S evidence theory and cooperative game theory, respectively. Zheng [117] constructed a data sensing system for diesel engine performance evaluation, created a prediction model for key condition parameters of diesel engines, proposed a method for diesel engine whole engine performance evaluation based on the hierarchical analysis method and SVM, and developed a platform for diesel engine whole engine performance evaluation. Proportional risk models are widely used in reliability engineering to describe the effects of life and covariates (temperature and vibration) on time to failure. Zheng et al. [118] constructed an iterative algorithm to approximate the health status of a system based on a proportional risk model with Markov properties for covariate processes. Zhang [119] completed the overall design of a data management system for diesel engine health status monitoring and assessment. A modular approach was used to design the diesel engine embedded machine-side control subsystem, the health status online monitoring subsystem, and the health status offline analysis subsystem, and to determine the way of data interaction between the subsystems. Liu et al. [120] proposed an adaptive noise reduction and multi-channel information fusion method for diesel engine valve clearance health status assessment. Ke et al. [121] investigated the extraction of diesel engine valve clearance degradation features based on the fusion of CEEMDAN and discriminant correlation analysis features, and the fused degradation features were fed into a LS SVM to achieve health status assessment. Wang et al. [122] used combinatorial rules to fuse the evaluation results of multiple

CNNs to construct an intelligent health status evaluation model for diesel engines called a random CNN.

Unlike the status assessment of components, the health status assessment of a diesel engine or subsystem needs to consider both its horizontal degradation (the interaction and degradation trend of components at the same level) and its vertical degradation (the impact of the degradation of components at lower levels on components at higher levels). The knowledge-driven approach has the advantage of low complexity as it can model the horizontal and vertical degradation processes of a diesel engine or subsystem based on domain expert knowledge; however, fuzzy prior knowledge reduces the accuracy of the health status assessment model, and a static knowledge-based assessment model cannot characterize the dynamic degradation process of the diesel engine. The model-driven method has a clear physical meaning but requires a high level of accuracy in the construction of mathematical analytical models. The data-driven method requires a large amount of condition monitoring data and has the advantages of high accuracy and no need for expert knowledge, but the health status assessment models constructed based on the data-driven method lack clear physical interpretation and are susceptible to interference from noise and abnormal samples.

With the diversification of diesel engine operation scenarios and the complexity of functional requirements, the existing research results suffer from weak transferability to unknown working conditions and a strong reliance on complete expert experience, neglecting the multi-types of knowledge in variable working condition operation scenarios, which limits the engineering application effect of the existing results. Therefore, how to effectively utilize multi-source knowledge, construct a retrospective correction mechanism for actual working scenarios, and achieve multi-way optimization between different assessment mechanisms through the intersection of multiple knowledge sources is an effective method to break through the bottleneck of health status assessment research applications. Analyzed from the perspective of the data sources that can be utilized, the multi-source features that can be used for diesel engine health status assessment are shown in Figure 8.

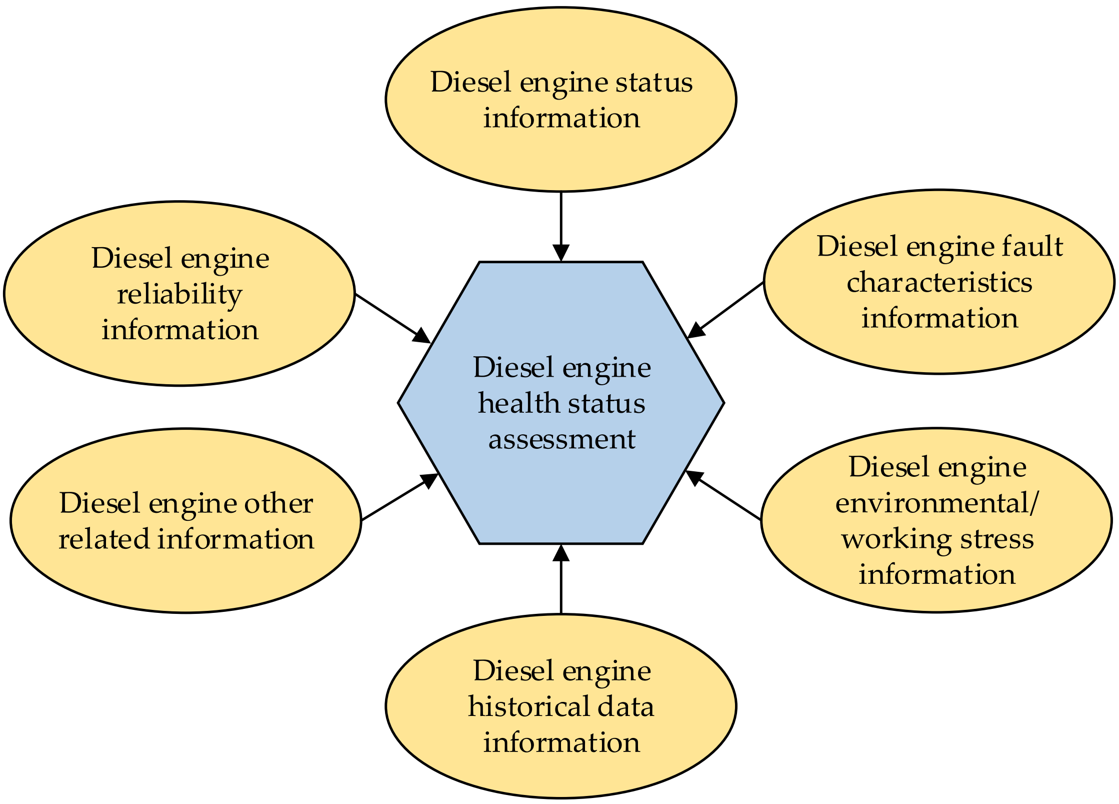


Figure 8. Multi-source characterization of diesel engine health status assessment.

With the multi-source features in Figure 8, how to weight and fuse the assessment feature information is the core and most difficult part of diesel engine health status assessment. With the development of advanced technologies such as big data processing, artificial intelligence, data mining, and information fusion, the performance of diesel engine health status assessment will be effectively improved.

According to the multi-source characteristics of diesel engine health status assessment, it is vital to divide the diesel engine health status classes reasonably and effectively. The classification of diesel engine health status classes should conform to the following principles:

1. Clear purpose and detailed hierarchy: the classification of the health status of diesel engines should be combined with the purpose of health status assessment, and the health status classification should be detailed and reasonable;
2. Concise and usable: The name of the health status classification should be simple and concise. The health status classification should make the assessment results highly usable;
3. Separate and easily distinguishable status: each health status should have separate status intervals from each other, with no overlap or crossover in the range of health status levels.

By analyzing the multi-source characteristics and classification of diesel engine health status assessment, the aim is to provide some reference for diesel engine health status assessment work so that diesel engine health management can be carried out effectively.

4. Challenges and Perspectives in Diesel Engine Equipment PHM

As the field of PHM for diesel engine equipment enters the era of big data, the requirements for adaptiveness and intelligence of key technologies are increasing, and the research on PHM theoretical methods for diesel engine equipment is increasingly developed and improved. However, in view of the complexity of diesel engine equipment and the specificity of the application environment, the flexible application of PHM technology to the practical problems of diesel engine equipment engineering still faces many new challenges:

1. The existing technology for monitoring the condition of diesel engine equipment neglects the study of sensor layout optimization. A good sensor layout is the basic guarantee for accurate measurement of diesel engine condition information. In engineering applications, due to the limitations of experimental sites and economic conditions, how to meet the requirements of diesel engine measurability while minimizing sensor cost is an urgent problem for diesel engine PHM, with a view to obtaining the best balance between sensor distribution cost and system constraints;
2. The quality of diesel engine condition monitoring data is generally poor, including time delay, abnormality, missing data, noise, and so on, which makes it difficult to dig out effective condition characteristic information from low-quality monitoring data. Diesel engine condition monitoring data has the characteristics of multi-source heterogeneity, various forms of signal measurement point sampling, poor consistency, and more serious interference from random factors, which makes it more difficult to apply PHM key technologies to diesel engines;
3. Most of the existing diesel engine equipment fault diagnosis methods are based on closed-loop assumptions, i.e., the diagnostic effect of the model can only be guaranteed from known data. For unknown data, the models have poor generalization capabilities. Although transfer learning-based fault diagnosis can be performed on common features in different but related domains, there are still requirements for the acquisition of data in specific target domains, and there are still limitations in engineering applications;
4. Currently, supervised machine learning models with deterministic expressions are commonly used to assess the health status of diesel engine equipment. In engineering applications, the problem of uncertainty in health status assessment always exists. Due to the different service environments and operating conditions in each phase of the diesel engine's life, it is difficult to effectively evaluate the reliability and accuracy

of the deterministic expression assessment model, and the uncertainty of the model results is difficult to assess, which can easily lead to status misjudgment.

In view of the above-mentioned difficulties and challenges in the research of key technologies for diesel engine equipment PHM, the possible future research directions are summarized as follows:

1. Sensor multi-objective layout optimization method and multi-sensor feature fusion. The use of wireless miniature intelligent sensors to collect information on diesel engine equipment condition monitoring can effectively alleviate the constraints of the experimental site and improve the efficiency of information collection. The optimal balance between sensor distribution costs and system constraints is achieved by studying sensor layout optimization methods. Multi-sensor feature fusion technology is used to fuse the signal time, space, and physical features to obtain richer diesel engine operation data;
2. Standardization of condition monitoring data and quality assurance methods for diesel engine equipment. The establishment of a condition monitoring data quality assurance method system can effectively improve the adaptability of PHM technology to engineering application problems. Monitoring data quality assurance requires comprehensive consideration of data recovery, cleaning, regularization, and other methods. For different parts or physical quantities to be measured, data monitoring, transmission, and storage-related standards are developed to lay a solid data foundation for the efficient and reliable application of PHM technology to diesel engines;
3. A study of a fault diagnosis method for diesel engine equipment based on fusing data-driven and knowledge-driven. By embedding the constraints formed by the physical model and domain knowledge in the data-driven model to compensate for the shortcomings of a single data-driven model, the model learns to conform to the characteristics of physical rules and domain knowledge and improves the robustness and generalizability of the model. The fusion of data-driven and knowledge-driven models represented by physics-informed neural networks (PINN) provides a new idea for the research of key technologies of PHM for diesel engines;
4. Highly credible diesel engine equipment health status assessment framework construction. The condition level and degradation rule for diesel engines should consider the use time and environment of diesel engines and study the dynamic health status assessment model. Unlike the health status assessment of components, the health status assessment of diesel engine subsystems or the whole engine needs to consider both vertical and horizontal degradation. By integrating probabilistic modeling, uncertainty quantification, and statistics to build a highly credible framework, the reliability and generalization ability of the model will be improved, and ultimately, highly credible intelligent assessment will be achieved.

5. Conclusions

This paper conducts a research review on the PHM of diesel engine equipment. The development history of PHM is reviewed, the basic concept and main functions of PHM are introduced, the PHM architecture of diesel engines is constructed, the representative work and research status of PHM key technologies such as diesel engine condition monitoring, data processing, fault diagnosis, and health status assessment are sorted out and summarized, the challenges faced when applying PHM technology flexibly to the practical problems of diesel engine engineering are discussed, and possible future research directions for PHM key technologies for diesel engines are foreseen. This paper can provide some reference for researchers in the field related to PHM of diesel engine equipment and promote the research of theoretical methods of PHM of diesel engine equipment to transform them into practical engineering applications.

Although the research in this paper has achieved certain achievements, there are still several shortcomings that need to be improved in the following aspects:

1. In the existing studies, most of the diesel engine pre-set failure experiments have been conducted for a few typical failure modes in the fuel supply system, which are relatively homogeneous. The next step should be to carry out a more comprehensive study of each subsystem of the diesel engine;
2. Most of the existing studies have been carried out in a laboratory environment for a single operating condition context and have not investigated the effects of complex operating conditions (e.g., different power, speed, environment, etc.) on the diesel engine equipment. Therefore, the next step is to carry out research on complex working conditions;
3. The next step needs to be the study of remaining life prediction and maintenance decisions for diesel engines and needs to be more concretely implemented into the actual work of current diesel engine equipment maintenance support to provide a basis for relevant maintenance decision making.

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